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On the estimation of the expectation of a heavy-tail distribution

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Abstract

We use bias-reduced estimators of extreme quantiles from heavy-tail distributions, to build a new estimator of the expectation in the case of infinite second moment. The asymptotic normality of the proposed estimator is established under mild conditions.

Keywords: Extreme value theory; Heavy-tail distributions; Hill estimator; Regular variation; Tail index.

1 Introduction

Let $X_1, X_2, \dots$ be independent and identically distributed non-negative random variables with expectation $\mu < \infty$, variance σ^2 and cumulative distribution function (cdf) F . Suppose that the tail of F is regularly varying at infinity with tail index $(-\alpha) < 0$, that is

$$\lim_{t \rightarrow \infty} \frac{1 - F(tx)}{1 - F(t)} = x^{-\alpha}, \quad \text{for any } x > 0, \quad (1)$$

Such heavy-tail distributions include distributions such as Pareto, Burr, Student, α -stable ($0 < \alpha < 2$), and log-gamma, which are known to be appropriate models for fitting large insurance claims, large fluctuations of prices, log-returns, etc. We are concerned with the construction of a bias-reduced asymptotically normal estimator for the expectation

$$\mu := \int_0^\infty x dF(x),$$

which could be rewritten, in terms of the quantile function (corresponding to the cdf F)

$$Q(s) := \inf \{x : F(x) \geq s\}, \quad 0 < s < 1,$$

as

$$\mu = \int_0^1 Q(1-s) ds. \quad (2)$$

For a given sample $X_1, \dots, X_n$, let

$$Q_n(s) := \inf \{x \in \mathbb{R} : F_n(x) \geq s\}, \quad 0 < s \leq 1,$$

denote the sample quantile function (classical non-parametric estimator of Q) associated to the empirical cdf defined on the real line by $F_n(x) := n^{-1} \sum_{i=1}^n \mathbb{I}(X_i \leq x)$, with $\mathbb{I}(\cdot)$ being the indicator function. The natural (unbiased) estimator of μ is the sample mean

$$\int_0^1 Q_n(1-s) ds = \frac{1}{n} \sum_{i=1}^n X_i =: \bar{X}_n. \quad (3)$$

From the Central Limit Theorem (CLT), the sequence of r.v.'s $\{\sqrt{n}(\bar{X}_n - \mu)/\sigma, n \geq 1\}$ converges in distribution to the standard Gaussian r.v., provided that the second-order moment $\mathbf{E}[X_1^2]$ is finite. This is a very restrictive condition in the context of heavy-tail distributions as the following considerations show. Assume that the r.v. X_1 follows the Pareto law with index $\alpha > 0$, that is, $1 - F(x) = x^{-\alpha}$ for $x \geq 1$. When $\alpha > 1$, the expectation μ exists, but $\mathbf{E}[X_1^2]$ is only finite for $\alpha \geq 2$. Hence, the range $\alpha \in (1, 2)$ is not covered by the CLT and thus we need to seek another approach to handle this situation. Making use of Weissman's estimator of high quantiles an alternative estimator for μ was proposed and its asymptotic normality was established for any $\alpha \in (1, 2)$. Let us define the following estimator for Q :

$$\hat{Q}_n(1-s) := \begin{cases} Q_n^W(1-s) & \text{for } 0 < s < k/n \\ Q_n(1-s) & \text{for } k/n \leq s < 1, \end{cases}$$

where

$$Q_n^W(1-s) := (k/n)^{1/\hat{\alpha}_n^H} X_{n-k,n} s^{-1/\hat{\alpha}_n^H}, \quad s \downarrow 0 \quad (4)$$

is Weissman's estimator of high quantiles, with

$$\hat{\alpha}_n^H := \left(k^{-1} \sum_{i=1}^k \log X_{n-i+1,n} - \log X_{n-k,n} \right)^{-1}, \quad (5)$$

being the well-known Hill estimator of the tail index α , and $X_{1,n} \leq \dots \leq X_{n,n}$ denoting the order statistics pertaining to the sample $X_1, \dots, X_n$. The number k represents the number of upper order statistics used in the computation of $\hat{\alpha}_n^H$, it is an integer sequence $k = k_n$ satisfying

$$1 < k < n, \quad k \rightarrow \infty \text{ and } k/n \rightarrow 0 \text{ as } n \rightarrow \infty. \quad (6)$$

By replacing $Q(1-s)$ by $\hat{Q}_n(1-t)$ in formula (2), an alternative estimator for μ is as follows:

$$\hat{\mu}_n^P = \hat{\mu}_n^P(k) := \int_0^1 \hat{Q}_n(1-s) ds = \int_0^{k/n} Q_n^W(1-s) ds + \int_{k/n}^1 Q_n(1-s) ds,$$

which, by a straightforward calculation, is equal to

$$\hat{\mu}_n^P := \frac{k}{n} \frac{\hat{\alpha}_n^H}{\hat{\alpha}_n^H - 1} X_{n-k,n} + \frac{1}{n} \sum_{i=k+1}^n X_{n-i+1,n}, \quad (7)$$

provided that $\hat{\alpha}_n^H > 1$. Moreover, the same author showed that, under suitable regularity assumptions, for any $\alpha \in (1, 2)$,

$$\frac{\sqrt{n}(\hat{\mu}_n^P - \mu)}{\sqrt{k/n}X_{n-k,n}} \xrightarrow{d} \mathcal{N}(0, \sigma^2(\alpha)), \text{ as } n \rightarrow \infty, \quad (8)$$

where

$$\sigma^2(\alpha) := \alpha / (1 - \alpha)^4 (2 - \alpha).$$

Throughout this paper, the standard notations $\xrightarrow{p}$, $\xrightarrow{d}$ and $\stackrel{d}{=}$ respectively stand for convergence in probability, convergence in distribution and equality in distribution, while $\mathcal{N}(a, b^2)$ denotes the normal distribution with expectation a and variance b^2 .

Actually, this estimator is defined in the more general situation where the r.v. X is real (not necessarily non-negative) with lower and upper heavy tails. He simultaneously took into account the regular variations of both tails of G and the balance condition

$$\lim_{t \rightarrow \infty} (1 - F(t)) / (1 - F(t) - F(-t)) = p \in [0, 1].$$

In this paper, we only consider non-negative r.v.'s. Our motivation comes from the actuarial risk theory where insurance losses are represented by such r.v.'s. In this case, $\hat{\mu}_n^P$ may be interpreted as an estimator of a risk measure called the net premium. Note that in our case, since r.v. X is non-negative, we have $F(-x) = 0$ for $x \geq 0$, which yields $p = 1$ in the above balance condition.

Hill's estimator $\hat{\alpha}_n^H$ plays a pivotal role in statistical inference on distribution tails. This estimator has been thoroughly studied, improved and even generalized to any real parameter α . Weak consistency of $\hat{\alpha}_n^H$ was established assuming only that the underlying cdf F satisfies condition (1). The asymptotic normality of $\hat{\alpha}_n^H$ has been established under the following stricter condition that characterizes Hall's model.

$$1 - F(x) = cx^{-\alpha} + dx^{-\beta} + o(x^{-\beta}), \text{ as } x \rightarrow \infty, \quad (9)$$

for some $c > 0$, $d \neq 0$ and $\beta > \alpha > 0$. Note that (9), which is a special case of a more general second-order regular variation condition, is equivalent to

$$Q(1 - s) = c^{1/\alpha} s^{-1/\alpha} \left(1 + \alpha^{-1} c^{-\beta/\alpha} d s^{\beta/\alpha - 1} + o(1) \right), \text{ as } s \downarrow 0. \quad (10)$$

The constants α and β are called, respectively, first-order (tail index, shape parameter) and second-order parameters of cdf F .

Extreme value based estimators essentially rely on the number k of upper order statistics involved in estimate computation. Hill's estimator has, in general, a substantial variance for small values of k and a considerable bias for large values of k . Hence, one has to look for a k value, denoted by k^* , that balances between these two vices. The choice of this optimal value k^* represents

a thorny issue in the process of estimating the tail index and related quantities. To solve this problem, several adaptive procedures are available. A theoretical optimal choice of k is obtained by minimizing the asymptotic mean squared error (RMSE) of $\hat{\alpha}_n^H$. Indeed, under condition (9), we have

$$k^* := \left(2^{-1} \alpha \beta^2 (\beta - \alpha)^{-3} d^{-2} c^{2\beta/\alpha} \right)^{\frac{\alpha}{2\beta-\alpha}} n^{\frac{2\beta-2\alpha}{2\beta-\alpha}}. \quad (11)$$

Though Peng's estimator $\hat{\mu}_n^P$ enjoys the asymptotic normality property, it still has a problem due to the fact that, it is based on Weissman's estimator Q_n^W known to be largely biased. Fortunately, many estimators with reduced biases are proposed in the literature as an alternative to Q_n^W .

In this paper, we use the bias-reduced estimator of the high quantile $Q(1-s)$, recently proposed by who exploited the censored maximum likelihood (CML) based estimators $(\hat{\alpha}, \hat{\beta})$ of the couple of regular variation parameters (α, β) . The CML estimators $(\hat{\alpha}, \hat{\beta})$ are defined as the solution of the two equations (under the constraint $\beta > \hat{\alpha}_n^H$)

$$\frac{1}{k} \sum_{i=1}^k \frac{1}{G_i(\alpha, \beta)} = 1 \quad \text{and} \quad \frac{1}{k} \sum_{i=1}^k \frac{1}{G_i(\alpha, \beta)} \log \frac{X_{n-i+1,n}}{X_{n-k,n}} = \beta^{-1}, \quad (12)$$

where

$$G_i(\alpha, \beta) = \frac{\alpha}{\beta} \left(1 + \frac{\alpha\beta}{\alpha - \beta} H(\alpha) \right) \left(\frac{X_{n-i+1,n}}{X_{n-k,n}} \right)^{\beta-\alpha} - \frac{\alpha\beta}{\alpha - \beta} H(\alpha), \quad (13)$$

with

$$H(\alpha) = \frac{1}{\alpha} - \frac{1}{k} \sum_{i=1}^k \log \frac{X_{n-i+1,n}}{X_{n-k,n}}.$$

The bias-reduced estimators $Q_n^{LPY}(1-s)$, of the high quantiles $Q(1-s)$, are obtained by substituting $(\hat{\alpha}, \hat{\beta})$ to (α, β) in (10). That is

$$Q_n^{LPY}(1-s) := \hat{c}^{1/\hat{\alpha}} s^{-1/\hat{\alpha}} \left(1 + \hat{\alpha}^{-1} \hat{c}^{-\hat{\beta}/\hat{\alpha}} \hat{d} s^{\hat{\beta}/\hat{\alpha}-1} \right), \quad s \downarrow 0, \quad (14)$$

where

$$\begin{cases} \hat{c} = \frac{\hat{\alpha}\hat{\beta}}{\hat{\alpha} - \hat{\beta}} \frac{k}{n} X_{n-k,n}^{\hat{\alpha}} \left(\frac{1}{\hat{\beta}} - \frac{1}{k} \sum_{i=1}^k \log \frac{X_{n-i+1,n}}{X_{n-k,n}} \right), \\ \hat{d} = \frac{\hat{\alpha}\hat{\beta}}{\hat{\beta} - \hat{\alpha}} \frac{k}{n} X_{n-k,n}^{\hat{\beta}} \left(\frac{1}{\hat{\alpha}} - \frac{1}{k} \sum_{i=1}^k \log \frac{X_{n-i+1,n}}{X_{n-k,n}} \right). \end{cases} \quad (15)$$

The consistency and asymptotic normality of $Q_n^{LPY}(1-s)$ are established by the same authors. Now we can define another estimator for the quantile function Q as follows:

$$\tilde{Q}_n(1-s) = \begin{cases} Q_n^{LPY}(1-s) & \text{for } 0 < s < k/n \\ Q_n(1-s) & \text{for } k/n \leq s < 1. \end{cases}$$

By replacing Q by $\tilde{Q}_n$, in formula (2), we get

$$\hat{\mu}_n = \hat{\mu}_n(k) := \int_0^1 \tilde{Q}_n(1-s)ds = \int_0^{k/n} Q_n^{LPY}(1-s)ds + \int_{k/n}^1 Q_n(1-s)ds. \quad (16)$$

An elementary integral calculation leads to a new bias-reduced estimator for μ defined by the following formula:

$$\hat{\mu}_n := (k/n)(n\hat{c}/k)^{1/\hat{\alpha}} \left(\frac{\hat{\alpha}}{\hat{\alpha}-1} + \frac{\hat{d}\hat{c}^{-\hat{\beta}/\hat{\alpha}}(k/n)^{\hat{\beta}/\hat{\alpha}-1}}{\hat{\beta}-1} \right) + \frac{1}{n} \sum_{i=k+1}^n X_{n-i+1,n}, \quad (17)$$

provided that $\hat{\beta} > \hat{\alpha} > 1$ so that $\hat{\mu}_n$ be finite.

The rest of the paper is organized as follows. In Section 2, we briefly discuss the third order-condition of regular variation before establishing the asymptotic normality of $\hat{\mu}_n$. Some concluding remarks notes made in Section 4. Finally, some of the main results used in Section 3 are gathered in the Appendix.

2 Main results

In the theory of extremes, a function, denoted by U and (sometimes) called tail quantile function, is used quite often. It is defined by

$$U(t) := (1/(1-F))^{-1}(t) = Q(1-1/t), \quad 1 < t < \infty.$$

In terms of this function, Hall's conditions (9) and (10) are equivalent to

$$U(t) = c^{1/\alpha} t^{1/\alpha} \left(1 + \alpha^{-1} c^{-\beta/\alpha} dt^{1-\beta/\alpha} + o(1) \right), \quad t \rightarrow \infty. \quad (18)$$

This implies that

$$\lim_{t \rightarrow \infty} \frac{\log[U(tx)/U(t)] - \alpha^{-1} \log x}{A_1(t)} = \frac{x^{1-\beta/\alpha} - 1}{1 - \beta/\alpha}, \quad \text{for any } x > 0, \quad (19)$$

where

$$A_1(t) := d\alpha^{-1}(1 - \beta/\alpha)c^{-\beta/\alpha}t^{1-\beta/\alpha}.$$

The function $A_1(t)$, which tends to zero as $t \rightarrow \infty$ (because $\beta > \alpha$), determines the rate of convergence of $\log[U(tx)/U(t)]$ to its limit $\alpha^{-1} \log x$. Relation (19) is known as the second-order condition of regular variation.

Unfortunately, the second-order regular variation is not sufficient to find asymptotic distributions for the estimators defined by the systems (12) and (15). We strengthen it into a condition, called third-order condition of regular variation and given by (20), that specifies the rate of (19).

$$\lim_{t \rightarrow \infty} \frac{\frac{\log[U(tx)/U(t)] - \alpha^{-1} \log x}{A_1(t)} - \frac{x^{1-\beta/\alpha} - 1}{1 - \beta/\alpha}}{A_2(t)} = D(\alpha, \beta, \rho), \quad (20)$$

where $A_2(t) \rightarrow 0$ as $t \rightarrow \infty$, with constant sign near infinity and

$$D(\alpha, \beta, \rho) := \frac{1}{\rho} \left(\frac{x^{1-\beta/\alpha+\rho} - 1}{1 - \beta/\alpha + \rho} - \frac{x^{1-\beta/\alpha} - 1}{1 - \beta/\alpha} \right),$$

with ρ being a positive constant called third-order parameter. The asymptotic normality of $\hat{\alpha}$, $\hat{\beta}$ and $\hat{c}$ was established under the following extract conditions on the sample fraction k , as $n \rightarrow \infty$,

$$(i) \sqrt{k} |A_1(n/k)| \rightarrow \infty, \quad (ii) \sqrt{k} A_1^2(n/k) \rightarrow 0, \quad (iii) \sqrt{k} A_1(n/k) A_2(n/k) \rightarrow 0. \quad (21)$$

As for $\hat{d}$, it is asymptotically normal under the assumption $(\sqrt{k} |A_1(n/k)|) / \log(n/k) \rightarrow \infty$ added to (ii) and (iii).

Example 1 Consider the Fréchet cdf with shape parameter $\alpha > 0$

$$F(x) = \exp(-x^{-\alpha}), \quad x > 0. \quad (22)$$

The corresponding tail quantile function is defined by $U(t) = (-\log(1 - 1/t))^{-1/\alpha}$, for $t > 1$. Applying Taylor's expansion (to the third order) to U and identifying with (18), yield $\beta = 2\alpha$, $c = 1$ and $d = -1/2$. The condition (20) holds for $A_1(t) = t^{-1}/2\alpha$, $A_2(t) = (\alpha - 3)t^{-2}/12\alpha^2$ and $\rho = 3\alpha$.

Note that, from a theoretical point of view, assumptions (6) and (21) are realistic, as the following example shows. Indeed, let us choose $k = [n^\epsilon]$, $0 < \epsilon < 1$, then it easy to verify that these assumptions hold for any $2/3 < \epsilon < 4/5$. The notation $[\cdot]$ stands for the integer part of real numbers.

Our main result, namely the asymptotic normality of the bias-reduced estimator $\hat{\mu}_n$, is formulated in the last of the following four theorems. In Theorem 1, we give an approximation of $\hat{\alpha}$ in terms of Brownian bridges, which leads to its asymptotic normality stated in Theorem 2. We do the same thing to $\hat{\mu}_n$ in Theorem 3. But, this does not meet our needs to achieve the major object of this paper. Then, we need to approximate both $\hat{\alpha}$ and $\hat{\mu}_n$ by linear functional of the same sequence of standard Brownian bridges $B_n(s)$.

Theorem 1 Assume that the third order condition (20) holds with $\beta/\alpha =: \lambda > 1$ and let $k = k_n$ be an integer sequence satisfying (6) and (21). Then there exists a sequence of Brownian bridges $\{B_n(s), 0 \leq s \leq 1\}$ such that

$$\sqrt{k}(\hat{\alpha} - \alpha) = \alpha(\eta_1 W_{1n} + \eta_2 W_{2n} + \eta_3 W_{3n}) + o_p(1), \quad \text{as } n \rightarrow \infty$$

where W_{1n} , W_{2n} and W_{3n} are sequences of centered Gaussian r.v.'s defined by

$$\begin{aligned} W_{1n} &:= \sqrt{n/k} B_n(1 - k/n) - \sqrt{n/k} \int_0^1 s^{-1} B_n(1 - ks/n) ds, \\ W_{2n} &:= (\lambda^{-1} - 1) \sqrt{n/k} B_n(1 - k/n) + (\lambda - 1) \sqrt{n/k} \int_0^1 s^{\lambda-2} B_n(1 - ks/n) ds, \\ W_{3n} &:= (1 - \lambda) \sqrt{n/k} \int_0^1 s^{\lambda-2} (\log s) B_n(1 - ks/n) ds \\ &\quad + \lambda^{-2} \sqrt{n/k} B_n(1 - k/n) - \sqrt{n/k} \int_0^1 s^{\lambda-2} B_n(1 - ks/n) ds, \end{aligned}$$

and

$$\eta_1 := \frac{\lambda^4}{(\lambda - 1)^4}, \quad \eta_2 := \frac{\lambda^2(2\lambda - 1)(3\lambda - 1)}{(\lambda - 1)^5}, \quad \eta_3 := \frac{\lambda^3(2\lambda - 1)^2}{(\lambda - 1)^4}.$$

Theorem 2 Under the assumptions of Theorem 1, we have

$$\sqrt{k}(\hat{\alpha} - \alpha) \xrightarrow{d} \mathcal{N}\left(0, \alpha^2 \beta^4 / (\alpha - \beta)^4\right), \text{ as } n \rightarrow \infty. \quad (23)$$

Theorem 3 Under the assumptions of Theorem 1, we have, as $n \rightarrow \infty$

$$\frac{\sqrt{n}}{\sqrt{k/n} (nc/k)^{1/\alpha}} \{\hat{\mu}_n - \mu\} = -\frac{\alpha}{(\alpha - 1)^2} \{\eta_1 W_{1n} + \eta_2 W_{2n} + \eta_3 W_{3n}\} + W_{4n} + o_p(1),$$

where W_{1n} , W_{2n} and W_{3n} are those of Theorem 1 and

$$W_{4n} := -\frac{\int_{k/n}^1 B_n(1 - s) dQ(1 - s)}{\sqrt{k/n} (nc/k)^{1/\alpha}}.$$

Theorem 4 Under the assumptions of Theorem 1, we have

$$\frac{\sqrt{n}}{\sqrt{k/n} (nc/k)^{1/\alpha}} \{\hat{\mu}_n - \mu\} \xrightarrow{d} \mathcal{N}(0, \sigma^2(\alpha, \beta)), \text{ as } n \rightarrow \infty, \quad (24)$$

where

$$\sigma^2(\alpha, \beta) := \frac{\alpha^2 \beta^4}{(\alpha - 1)^4 (\alpha - \beta)^4} + \frac{2}{2 - \alpha} + \frac{2\alpha \beta^2}{(\alpha - 1)^2 (\alpha - \beta)^2}. \quad (25)$$

The following corollary to Theorem 4 provides a straightforward practical way to build confidence intervals for μ .

Corollary 1 Under the assumptions of Theorem 1, we have

$$\frac{\sqrt{n}}{\sqrt{k/n\sigma}(\hat{\alpha}, \hat{\beta})(n\hat{c}/k)^{1/\hat{\alpha}}} \{\hat{\mu}_n - \mu\} \xrightarrow{d} \mathcal{N}(0, 1), \text{ as } n \rightarrow \infty,$$

where $\hat{\alpha}$, $\hat{\beta}$ and $\hat{c}$ are the estimates of α , β and c given in (12) and (15) respectively.

3 Proofs

3.1 Proof of Theorem 1.

First recall that $\lambda = \beta/\alpha > 1$. Then, we have, as $n \rightarrow \infty$

$$\hat{\alpha} - \alpha = \alpha \left\{ \eta_1 (S_1 - 1) + \eta_2 (S_2 - \lambda^{-1}) + \eta_3 (S_3 - \lambda^{-2}) \right\} + o_p \left(k^{-1/2} \right), \quad (26)$$

where

$$S_1 := \frac{1}{k} \sum_{i=1}^k \log \frac{Y_{n-i+1,n}}{Y_{n-k,n}}, \quad S_2 := \frac{1}{k} \sum_{i=1}^k \left(\frac{Y_{n-i+1,n}}{Y_{n-k,n}} \right)^{1-\lambda}, \quad (27)$$

and

$$S_3 := \frac{1}{k} \sum_{i=1}^k \left(\frac{Y_{n-i+1,n}}{Y_{n-k,n}} \right)^{1-\lambda} \log \frac{Y_{n-i+1,n}}{Y_{n-k,n}}, \quad (28)$$

with $Y_{1,n} \leq \dots \leq Y_{n,n}$ being the order statistics pertaining to a sample $Y_1, \dots, Y_n$ of independent and identically distributed non-negative random variables, defined on the same probability space as the X'_i 's, with cdf

$$G(y) = 1 - y^{-1}, \text{ for } y > 1. \quad (29)$$

A probability space $(\Omega, \mathcal{A}, \mathbf{P})$ may be constructed, carrying an infinite sequence $U_1, U_2, \dots$ of independent $(0, 1)$ -uniform r.v.'s and a sequence of Brownian bridges $\{B_n(s), 0 \leq s \leq 1\}$, $n = 1, 2, \dots$, having, amongst others, the property stated in Lemma 1. Let $U_{1,n} \leq \dots \leq U_{n,n}$ denote the order statistics pertaining to $U_1, \dots, U_n$ and define the empirical quantile function $V_n(s)$ as

$$V_n(s) = U_{i,n} \quad \text{for } (i-1)/n < s \leq i/n, \quad i = 1, \dots, n, \quad \text{and } V_n(0) = U_{1,n}.$$

Lemma 1 *On this probability space, for every $0 \leq \tau < 1/2$, we have, as $n \rightarrow \infty$*

$$\sup_{1/n \leq s \leq 1-1/n} \frac{|\sqrt{n}(s - V_n(s)) - B_n(s)|}{(s(1-s))^{1/2-\tau}} = O_p(n^{-\tau}). \quad (30)$$

Without loss of generality, we assume that

$$Y_i = G^{-1}(U_i) = (1 - U_i)^{-1}, \quad i = 1, \dots, n,$$

and

$$Y_{i,n} = G^{-1}(U_{i,n}) = (1 - U_{i,n})^{-1}, \quad i = 1, \dots, n,$$

where G^{-1} denotes the quantile function pertaining to cdf G given by formula (29). Then, this allows us to write

$$Y_{n-i+1,n} = (1 - V_n(1-s))^{-1}, \quad \text{for } \frac{i-1}{n} < s \leq \frac{i}{n}, \quad i = 1, \dots, n.$$

Making use of the previous representation of the order statistics $Y_{n-i+1,n}$, we may rewrite the three statistics in (27) and (28) into

$$\begin{aligned} S_1 &= \frac{n}{k} \int_0^{k/n} \log \left(\frac{1 - V_n(1-s)}{1 - U_{n-k,n}} \right)^{-1} ds, \\ S_2 &= \frac{n}{k} \int_0^{k/n} \left(\frac{1 - V_n(1-s)}{1 - U_{n-k,n}} \right)^{-1+\lambda} ds, \end{aligned}$$

and

$$S_3 = \frac{n}{k} \int_0^{k/n} \left(\frac{1 - V_n(1-s)}{1 - U_{n-k,n}} \right)^{-1+\lambda} \log \left(\frac{1 - V_n(1-s)}{1 - U_{n-k,n}} \right)^{-1} ds.$$

Next, we show that, as $n \rightarrow \infty$

$$\begin{aligned} \sqrt{k}(S_1 - 1) &= W_{1n} + o_p(1), \\ \sqrt{k}(S_2 - \lambda^{-1}) &= W_{2n} + o_p(1), \end{aligned}$$

and

$$\sqrt{k}(S_3 - \lambda^{-2}) = W_{3n} + o_p(1),$$

where W_{1n}, W_{2n} and W_{3n} are the Gaussian r.v.'s defined in Theorem 1. We will only consider the asymptotic distribution of S_3 . The proofs for S_1 and S_2 use similar arguments. By letting $f(x) = x^{\lambda-1} \log x$, the statistic S_3 becomes

$$S_3 = -(n/k) \int_0^{k/n} f \left(\frac{1 - V_n(1-s)}{1 - U_{n-k,n}} \right) ds.$$

An application of standard calculus gives $\int_0^1 f(s) ds = -\lambda^{-2}$. Therefore

$$S_3 - \lambda^{-2} = -(n/k) \int_0^{k/n} \left[f \left(\frac{1 - V_n(1-s)}{1 - U_{n-k,n}} \right) - f \left(\frac{s}{k/n} \right) \right] ds.$$

We divide the integral above in two parts, then we study the asymptotic behavior of each integral. Observe that

$$\begin{aligned} S_3 - \lambda^{-2} &= -(n/k) \int_0^{1/n} \left[f \left(\frac{1 - V_n(1-s)}{1 - U_{n-k,n}} \right) - f \left(\frac{s}{k/n} \right) \right] ds \\ &\quad - (n/k) \int_{1/n}^{k/n} \left[f \left(\frac{1 - V_n(1-s)}{1 - U_{n-k,n}} \right) - f \left(\frac{s}{k/n} \right) \right] ds \\ &=: -\Delta_n - \Omega_n. \end{aligned}$$

Next, we show that $\sqrt{k}\Delta_n$ converges to 0 in probability. Indeed, we have $1 - V_n(1-s) = 1 - U_{n,n}$, for $0 < s \leq 1/n$, it follows that

$$\begin{aligned} \Delta_n &= (n/k) \int_0^{1/n} \left[f \left(\frac{1 - U_{n,n}}{1 - U_{n-k,n}} \right) - f \left(\frac{s}{k/n} \right) \right] ds \\ &= k^{-1} f \left(\frac{1 - U_{n,n}}{1 - U_{n-k,n}} \right) - \int_0^{1/k} f(s) ds. \end{aligned}$$

An elementary calculation gives $\int_0^{1/k} f(s) ds = \lambda^{-1} k^{-\lambda} (\log k^{-1} - \lambda^{-1})$, and we have $n(1 - U_{n,n-k})/k \xrightarrow{P} 1$, as $n \rightarrow \infty$, therefore

$$\Delta_n = \{1 + o_p(1)\} k^{-\lambda} \log k^{-1} - \lambda^{-1} k^{-\lambda} (\log k^{-1} - \lambda^{-1}).$$

Since $\lambda > 1$ and $k \rightarrow \infty$, then $k^{-\lambda+1/2} \rightarrow 0$ and $k^{-\lambda+1/2} \log k^{-1} \rightarrow 0$, it follows that $\sqrt{k} \Delta_n \xrightarrow{P} 0$ as $n \rightarrow \infty$. Consider now the second term Ω_n which may be rewritten into

$$\begin{aligned} \Omega_n &= (n/k) \int_{1/n}^{k/n} \left[f\left(\frac{1 - V_n(1-s)}{1 - U_{n-k,n}}\right) - f\left(\frac{s}{1 - U_{n-k,n}}\right) \right] ds \\ &\quad + (n/k) \int_{1/n}^{k/n} \left[f\left(\frac{s}{1 - U_{n-k,n}}\right) - f\left(\frac{s}{k/n}\right) \right] ds \\ &=: \Omega_{n1} + \Omega_{n2}. \end{aligned}$$

Making use of Taylor's expansion of f , we get

$$f\left(\frac{1 - V_n(1-s)}{1 - U_{n-k,n}}\right) - f\left(\frac{s}{1 - U_{n-k,n}}\right) = f'\left(\frac{\varphi_n(s)}{1 - U_{n-k,n}}\right) \left(\frac{1 - V_n(1-s)}{1 - U_{n-k,n}} - \frac{s}{1 - U_{n-k,n}}\right),$$

and

$$f\left(\frac{s}{1 - U_{n-k,n}}\right) - f\left(\frac{s}{k/n}\right) = f'(s\psi_n) \left(\frac{s}{1 - U_{n-k,n}} - \frac{s}{k/n}\right),$$

where

$$\min\{1 - V_n(1-s), s\} < \varphi_n(s) < \max\{1 - V_n(1-s), s\} \quad (31)$$

and

$$\min\left\{\frac{1}{1 - U_{n-k,n}}, \frac{1}{k/n}\right\} < \psi_n < \max\left\{\frac{1}{1 - U_{n-k,n}}, \frac{1}{k/n}\right\}. \quad (32)$$

Observe now that Ω_{n1} and Ω_{n2} may be rewritten into

$$\Omega_{n1} = (n/k) \int_{1/n}^{k/n} f'\left(\frac{s}{1 - U_{n-k,n}}\right) \left[\frac{1 - V_n(1-s)}{1 - U_{n-k,n}} - \frac{s}{1 - U_{n-k,n}}\right] ds + \Omega_{n1}^*,$$

and

$$\Omega_{n2} = \{1 + o_p(1)\} (n/k) \int_{1/n}^{k/n} f'\left(\frac{s}{k/n}\right) \left[\frac{s}{1 - U_{n-k,n}} - \frac{s}{k/n}\right] ds + \Omega_{n2}^*,$$

where

$$\begin{aligned} \Omega_{n1}^* &:= (n/k) \int_{1/n}^{k/n} \left[f'\left(\frac{\varphi_n(s)}{1 - U_{n-k,n}}\right) - f'\left(\frac{s}{1 - U_{n-k,n}}\right) \right] \\ &\quad \times \left[\frac{1 - V_n(1-s)}{1 - U_{n-k,n}} - \frac{s}{1 - U_{n-k,n}} \right] ds, \end{aligned}$$

and

$$\begin{aligned}\Omega_{n2}^* := & \{1 + o_p(1)\} (n/k) \int_{1/n}^{k/n} \left[f' \left(\frac{s\psi_n}{k/n} \right) - f' \left(\frac{s}{k/n} \right) \right] \\ & \times \left[\frac{s}{1 - U_{n-k,n}} - \frac{s}{k/n} \right] ds.\end{aligned}$$

From Lemma 3 (see the Appendix), both $\sqrt{k}\Omega_{n1}^*$ and $\sqrt{k}\Omega_{n2}^*$ converge to 0 in probability. Since $n(1 - U_{n-k,n})/k \xrightarrow{P} 1$, then

$$\Omega_{n1} = \{1 + o_p(1)\} \int_{1/n}^{k/n} f' \left(\frac{s}{k/n} \right) [1 - s - V_n(1 - s)] ds + o_p(k^{-1/2}),$$

and

$$\Omega_{n2} = -\{1 + o_p(1)\} \frac{k/n - (1 - U_{n-k,n})}{(k/n)^2} \int_{1/n}^{k/n} \left(\frac{s}{k/n} \right) f' \left(\frac{s}{k/n} \right) ds + o_p(k^{-1/2}).$$

The derivative of function f equals $f'(x) = (\lambda - 1)x^{\lambda-2} \log x + x^{\lambda-2}$, then

$$\begin{aligned}\Omega_{n1} = & (\lambda - 1) (n/k) \int_{1/k}^1 t^{\lambda-2} (\log t) [1 - V_n(1 - kt/n) - kt/n] dt \\ & + (n/k) \int_{1/k}^1 t^{\lambda-2} [1 - V_n(1 - kt/n) - kt/n] dt + o_p(k^{-1/2}),\end{aligned}$$

and

$$\begin{aligned}\Omega_{n2} = & (\lambda - 1) (n/k) [k/n - (1 - U_{n-k,n})] \int_{1/k}^1 t^{\lambda-1} \log t dt \\ & + (n/k) [k/n - (1 - U_{n-k,n})] \int_{1/k}^1 t^{\lambda-1} dt + o_p(k^{-1/2}) \\ = & \lambda^{-2} (n/k) [k/n - (1 - U_{n-k,n})] + o_p(k^{-1/2}).\end{aligned}$$

Fix $0 < \tau < 1/2$, then using approximation (30), in Lemma 1, yields

$$\begin{aligned}\sqrt{k}\Omega_{n1} = & (\lambda - 1) \sqrt{n/k} \int_{1/k}^1 t^{\lambda-2} (\log t) B_n(1 - kt/n) dt \\ & + \sqrt{n/k} \int_{1/k}^1 t^{\lambda-2} B_n(1 - kt/n) dt + \sqrt{k}\tilde{\Omega}_{n1}(\tau) + o_p(1),\end{aligned}$$

and

$$\sqrt{k}\Omega_{n2} = -\lambda^{-2} \sqrt{n/k} B_n(1 - k/n) + \sqrt{k}\tilde{\Omega}_{n2}(\tau) + o_p(1),$$

where

$$\begin{aligned}\sqrt{k}\tilde{\Omega}_{n1}(\tau) = & (\lambda - 1) O_p(n^{-\tau}) (k/n)^{1/2-\tau} (n/k)^{1/2} \int_0^1 t^{\lambda-2+(1/2-\tau)} |\log t| dt \\ & + O_p(n^{-\tau}) (k/n)^{1/2-\tau} \sqrt{n/k} \int_0^1 t^{\lambda-2+(1/2-\tau)} dt,\end{aligned}$$

and

$$\sqrt{k}\tilde{\Omega}_{n2}(\tau) = \lambda^{-2}O_p(n^{-\tau})\sqrt{n/k}(k/n)^{1/2-\tau}.$$

For $\lambda > 1$, $\int_0^1 t^{\lambda-2+(1/2-\tau)} |\log t| dt = (\lambda - 1/2 - \tau)^{-2}$ and $\int_0^1 t^{\lambda-2+(1/2-\tau)} dt = (\lambda - 1/2 - \tau)^{-1}$ are finite integrals. Then both quantities $\sqrt{k}\tilde{\Omega}_{n1}$ and $\sqrt{k}\tilde{\Omega}_{n2}$ are equal to $O_p(k^{-\tau})$ for all large n , which tends in probability to 0 as $n \rightarrow \infty$. Recall that up to now we have showed that

$$\begin{aligned}\sqrt{k}\Omega_{n1} &= (\lambda - 1) \sqrt{n/k} \int_{1/k}^1 t^{\lambda-2} (\log t) B_n(1 - kt/n) dt \\ &\quad + \sqrt{n/k} \int_{1/k}^1 t^{\lambda-2} B_n(1 - kt/n) dt + o_p(1),\end{aligned}$$

and

$$\sqrt{k}\Omega_{n2} = \lambda^{-2} \sqrt{n/k} B_n(1 - k/n) + o_p(1).$$

It remains to prove that

$$\begin{aligned}I_n &:= (\lambda - 1) \sqrt{n/k} \int_0^{1/k} t^{\lambda-2} (\log t) B_n(1 - kt/n) dt \\ &\quad + \sqrt{n/k} \int_0^{1/k} t^{\lambda-2} B_n(1 - kt/n) dt,\end{aligned}$$

converges, in probability, to 0. Indeed, since $E|B_n(1 - ks/n)| \leq \sqrt{ks/n}$, then

$$\mathbf{E}|I_n| \leq (\lambda - 1) \int_0^{1/k} t^{\lambda-2+1/2} (|\log t| + 1) dt.$$

Since

$$\int_0^{1/k} t^{\lambda-2+1/2} (|\log t| + 1) dt = \frac{2}{(2\lambda - 1)^2} k^{-\lambda+\frac{1}{2}} (2\lambda - \log k + 2\lambda \log k + 1),$$

which tends to 0 as $n \rightarrow \infty$, then I_n converges to 0 in probability. This completes the proof of Theorem 1. $\square$

3.2 Proof of Theorem 2.

To establish the asymptotic normality of $\hat{\alpha}$, given in (23), we proceed by similar arguments as for $\hat{\mu}_n$ in the proof of Theorem 4. $\square$

3.3 Proof of Theorem 3

Let us divide the integral (2), in two parts, as follows:

$$\mu = \mu_{1,n}(k) + \mu_{2,n}(k),$$

where

$$\mu_{1,n}(k) := \int_0^{k/n} Q(1-s) ds \text{ and } \mu_{2,n}(k) := \int_{k/n}^1 Q(1-s) ds.$$

Recall that, in Section 1 formula (16), we have defined estimator $\hat{\mu}_n$ of μ by

$$\hat{\mu}_n = \hat{\mu}_{1,n}(k) + \hat{\mu}_{2,n}(k),$$

where

$$\hat{\mu}_{1,n}(k) := (k/n)(n\hat{c}/k)^{1/\hat{\alpha}} \left\{ \frac{\hat{\alpha}}{\hat{\alpha}-1} + \frac{\widehat{d\tilde{c}}^{-\hat{\beta}/\hat{\alpha}}(k/n)^{\hat{\beta}/\hat{\alpha}-1}}{\hat{\beta}-1} \right\}$$

and

$$\hat{\mu}_{2,n}(k) := \frac{1}{n} \sum_{i=k+1}^n X_{n-i+1,n}.$$

To simplify notations, let us set

$$Z_{ni} := \frac{\sqrt{n}}{\sqrt{k/n}(nc/k)^{1/\alpha}} \{\hat{\mu}_{i,n}(k) - \mu_{i,n}(k)\}, \quad i = 1, 2. \quad (33)$$

First, we consider Z_{n1} . It is easy to verify that, as $n \rightarrow \infty$

$$\mu_{1,n}(k) = \{1 + o_p(1)\} \frac{k}{n} (nc/k)^{1/\alpha} \frac{\alpha}{\alpha-1},$$

and, under the condition (6), we have

$$\hat{\mu}_{1,n}(k) = \{1 + o_p(1)\} \frac{k}{n} \frac{\hat{\alpha}}{\hat{\alpha}-1} (n\hat{c}/k)^{1/\hat{\alpha}}.$$

It follows that

$$\hat{\mu}_{1,n}(k) - \mu_{1,n}(k) = \{1 + o_p(1)\} \frac{k}{n} \left\{ \frac{\hat{\alpha}}{\hat{\alpha}-1} (n\hat{c}/k)^{1/\hat{\alpha}} - \frac{\alpha}{\alpha-1} (nc/k)^{1/\alpha} \right\}.$$

Let us write $Z_{n1} = T_{1n} + T_{2n}$, where

$$T_{1n} := \{1 + o_p(1)\} \sqrt{k} \left\{ \frac{\hat{\alpha}}{\hat{\alpha}-1} - \frac{\alpha}{\alpha-1} \right\},$$

and

$$T_{2n} := \{1 + o_p(1)\} \sqrt{k} \left\{ \frac{(n\hat{c}/k)^{1/\hat{\alpha}}}{(nc/k)^{1/\alpha}} - 1 \right\}.$$

We begin by showing that $T_{2n} \xrightarrow{P} 0$, as $n \rightarrow \infty$. First observe that T_{2n} may be rewritten into

$$T_{2n} = \{1 + o_p(1)\} \sqrt{k} \left\{ (nc/k)^{1/\hat{\alpha}-1/\alpha} (\hat{c}/c)^{1/\hat{\alpha}-1/\alpha} - 1 \right\}.$$

Assumptions (i) and (ii) of Theorem 1 imply that $k^{1/2}/\log(n/k) \rightarrow \infty$. Also, the asymptotic normality of $\hat{\alpha}$ gives $\hat{\alpha} - \alpha = O_p(k^{-1/2})$. Therefore $(1/\hat{\alpha} - 1/\alpha) \log(nc/k) \xrightarrow{P} 0$, this implies that $(nc/k)^{1/\hat{\alpha}-1/\alpha} \xrightarrow{P} 1$, as $n \rightarrow \infty$. On the other hand, we have

$$\hat{c}/c - 1 = \alpha^{-1} (\hat{\alpha} - \alpha) \log \frac{n}{k} + o_p\left(k^{-1/2} \log \frac{n}{k}\right).$$

Since $\hat{c}$ is a consistent estimator of c , then Taylor's expansion gives

$$(\hat{c}/c)^{1/\hat{\alpha}-1/\alpha} - 1 = \alpha^{-1} (1 + o_p(1)) (\hat{\alpha} - \alpha) (\hat{c}/c - 1), \text{ as } n \rightarrow \infty.$$

It suffices now to show that $\sqrt{k} \left((\hat{c}/c)^{1/\hat{\alpha}-1/\alpha} - 1 \right)$ converges to 0 in probability. Indeed, again by using the fact that $\hat{\alpha} - \alpha = O_p(k^{-1/2})$, yields

$$\sqrt{k} \left((\hat{c}/c)^{1/\hat{\alpha}-1/\alpha} - 1 \right) = O_p(1) \left(k^{-1/2} \log \frac{n}{k} + o_p \left(\frac{\log \frac{n}{k}}{\sqrt{k}} \right) \right),$$

which tends in probability to 0, because we already have $\sqrt{k}/\log(n/k) \rightarrow \infty$. Now, we consider the term T_{1n} . Since $\hat{\alpha}$ is a consistent estimator of α , then it is easy to show that

$$T_{1n} = -\frac{1 + o_p(1)}{(\alpha - 1)^2} \sqrt{k} (\hat{\alpha} - \alpha), \text{ as } n \rightarrow \infty.$$

From 1, we infer that

$$T_{1n} = -\frac{(1 + o_p(1))\alpha}{(\alpha - 1)^2} (\eta_1 W_{1n} + \eta_2 W_{2n} + \eta_3 W_{3n}), \text{ as } n \rightarrow \infty.$$

It follows that

$$Z_{n1} = -\frac{\alpha}{(\alpha - 1)^2} \{\eta_1 W_{1n} + \eta_2 W_{2n} + \eta_3 W_{3n}\} + o_p(1). \quad (34)$$

Let us now consider the asymptotic distribution of Z_{n2} , in (33). It is shown that

$$Z_{n2} = -\frac{\int_{k/n}^1 B_n(1-s) dQ(1-s)}{\sqrt{k/n} Q(1-k/n)} + o_p(1).$$

On the other hand, from (10), we have $Q(1-k/n) \sim (nc/k)^{1/\alpha}$, as $n \rightarrow \infty$, it follows that

$$Z_{n2} = W_{4n} + o_p(1). \quad (35)$$

Combining (34) and (35) achieves the proof of Theorem 3. $\square$

3.4 Proof of Theorem 4.

Now, we investigate the asymptotic normality of $\hat{\mu}_n$ given in (24). Since W_{in} , $i = 1, \dots, 4$ are sequences of centred Gaussian r.v.'s, then

$$\frac{\sqrt{n}}{\sqrt{k/n} (nc/k)^{1/\alpha}} \{\hat{\mu}_n - \mu\} \xrightarrow{d} \mathcal{N}(0, \Gamma \Sigma \Gamma^t), \text{ as } n \rightarrow \infty,$$

where

$$\Gamma := \left(-\frac{\alpha}{(\alpha - 1)^2} \eta_1, -\frac{\alpha}{(\alpha - 1)^2} \eta_2, -\frac{\alpha}{(\alpha - 1)^2} \eta_3, 1 \right),$$

Γ^t is the transpose of Γ and Σ is the variance-covariance matrix of the vector $(W_{1n}, \dots, W_{4n})$ defined by

$$\Sigma = \begin{bmatrix} 1 & \frac{1}{\lambda^2} - \frac{1}{\lambda} & \frac{2}{\lambda^3} - \frac{1}{\lambda^2} & -1 \\ \frac{1}{\lambda^2} - \frac{1}{\lambda} & \frac{1}{2\lambda-1} - \frac{1}{\lambda^2} & \frac{1}{(2\lambda-1)^2} - \frac{1}{\lambda^3} & \frac{\lambda-1}{\lambda} \\ \frac{2}{\lambda^3} - \frac{1}{\lambda^2} & \frac{1}{(2\lambda-1)^2} - \frac{1}{\lambda^3} & \frac{2}{(2\lambda-1)^3} - \frac{1}{\lambda^4} & -\frac{1}{\lambda^2} \\ -1 & \frac{\lambda-1}{\lambda} & -\frac{1}{\lambda^2} & \frac{2}{2-\alpha} \end{bmatrix}.$$

Note that the elements of Σ were obtained after tedious computations of the limits of the expectations $\mathbf{E}[W_{in}W_{jn}]$ for $i, j = 1, 4$ ($i \leq j$). Finally, a standard calculation of the product $\Gamma\Sigma\Gamma^t$ yields

$$\Gamma\Sigma\Gamma^t = \frac{\alpha^2\beta^4}{(\alpha-1)^4(\alpha-\beta)^4} + \frac{2}{2-\alpha} + \frac{2\alpha\beta^2}{(\alpha-1)^2(\alpha-\beta)^2},$$

which is denoted by $\sigma^2(\alpha, \beta)$. This completes the proof of Theorem 4. $\square$

4 Conclusion

The main objective of this paper was to propose a bias-reduced estimator for the expectation of a heavy-tail distribution. This was achieved on the basis of the bias-reduction of the first and second order parameter estimators of regularly varying distributions and the corresponding high quantiles estimators. In addition, the newly introduced estimator is asymptotically normal, making confidence intervals easily constructible.

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A Appendix: Auxiliary results

Lemma 2 Let $k = k_n$ be a sequence of integers satisfying (6) and $f(x) = x^{\lambda-1} \log x$, $\lambda > 1$. Then, uniformly on $s \in [1/n, k/n]$, we have

$$f' \left(\frac{\varphi_n(s)}{1 - U_{n-k,n}} \right) - f' \left(\frac{s}{1 - U_{n-k,n}} \right) = o_p(1) \left(\frac{s}{k/n} \right)^{\lambda-2} \log \frac{s}{k/n}, \text{ as } n \rightarrow \infty.$$

Proof. We have $n(1 - U_{n-k,n})/k \xrightarrow{p} 0$, as $n \rightarrow \infty$, then

$$f' \left(\frac{\varphi_n(s)}{1 - U_{n-k,n}} \right) - f' \left(\frac{s}{1 - U_{n-k,n}} \right) = (1 + o_p(1)) \left[f' \left(\frac{\varphi_n(s)}{k/n} \right) - f' \left(\frac{s}{k/n} \right) \right].$$

A straightforward calculation of the derivative of f yields

$$\begin{aligned} f' \left(\frac{\varphi_n(s)}{k/n} \right) - f' \left(\frac{s}{k/n} \right) &= \left(\frac{s}{k/n} \right)^{\lambda-2} \left[(\lambda-1) \left(\left(\frac{\varphi_n(s)}{s} \right)^{\lambda-2} - 1 \right) \log \frac{\varphi_n(s)}{k/n} \right. \\ &\quad \left. + (\lambda-1) \log \frac{\varphi_n(s)}{s} + \left(\frac{\varphi_n(s)}{s} \right)^{\lambda-2} - 1 \right]. \end{aligned} \quad (36)$$

Observe now, that inequalities (31) imply

$$\min \left\{ \frac{1-s-V_n(1-s)}{s}, 0 \right\} < \frac{\varphi_n(s)}{s} - 1 < \max \left\{ \frac{1-s-V_n(1-s)}{s}, 0 \right\}.$$

We have

$$\sup_{1/n \leq s < 1} \frac{|1-s-V_n(1-s)|}{s} \xrightarrow{p} 0 \text{ as } n \rightarrow \infty,$$

it follows that

$$\sup_{1/n \leq s \leq k/n} \left| \frac{\varphi_n(s)}{s} - 1 \right| \xrightarrow{p} 0 \text{ as } n \rightarrow \infty. \quad (37)$$

On the other hand, we infer that

$$\sup_{1/n \leq s \leq k/n} \left| \frac{s}{\varphi_n(s)} - 1 \right| \xrightarrow{p} 0 \text{ as } n \rightarrow \infty. \quad (38)$$

By applying the mean value theorem to the functions $x \rightarrow \log x$ and $x \rightarrow x^{\lambda-1}$ respectively, then by using (37) and (38), we show readily that, as $n \rightarrow \infty$

$$\sup_{1/n \leq s \leq k/n} \left| \log \frac{\varphi_n(s)}{s} \right| \xrightarrow{p} 0 \text{ and } \sup_{1/n \leq s \leq k/n} \left| \left(\frac{\varphi_n(s)}{s} \right)^{\lambda-1} - 1 \right| \xrightarrow{p} 0. \quad (39)$$

Note that the first result of (39) implies that

$$\sup_{1/n \leq s \leq k/n} \left| \log \frac{\varphi_n(s)}{k/n} - \log \frac{s}{k/n} \right| \xrightarrow{p} 0, \text{ as } n \rightarrow \infty. \quad (40)$$

By using equations (39) and (40) together, we show that, uniformly in $s \in [1/n, k/n]$, the right-hand side of equation (36), is equal to $o_p(1) \left(\frac{s}{k/n} \right)^{\lambda-2} \log \frac{s}{k/n}$. $\square$

Lemma 3 *We have $\sqrt{k}\Omega_{n1}^* \xrightarrow{p} 0$ and $\sqrt{k}\Omega_{n2}^* \xrightarrow{p} 0$, as $n \rightarrow \infty$.*

Proof. We only show the first result. The second one is obtained by similar arguments. Recall that

$$\begin{aligned} \Omega_{n1}^* &:= -(n/k) \int_{1/n}^{k/n} \left[f' \left(\frac{\varphi_n(s)}{1-U_{n-k,n}} \right) - f' \left(\frac{s}{1-U_{n-k,n}} \right) \right] \\ &\quad \times \left[\frac{1-V_n(1-s)}{1-U_{n-k,n}} - \frac{s}{1-U_{n-k,n}} \right] ds. \end{aligned}$$

Using Lemma 2, we get, as $n \rightarrow \infty$

$$\Omega_{n1}^* = o_p(1) (n/k) \int_{1/n}^{k/n} \left(\frac{s}{k/n} \right)^{\lambda-2} \left| \log \frac{s}{k/n} \right| \left| \frac{1 - V_n(1-s)}{k/n} - \frac{s}{k/n} \right| ds.$$

By a change of variables, we get

$$\Omega_{n1}^* = o_p(1) (n/k) \int_{1/k}^1 s^{\lambda-2} |\log s| |1 - V_n(1 - ks/n) - ks/n| ds.$$

Making use of approximation(30) yields

$$\sqrt{k}\Omega_{n1}^* = o_p(1) (n/k)^{1/2} \int_{1/k}^1 s^{\lambda-2} |\log s| \left(|B_n(1 - ks/n)| + (ks/n)^{1/2-\tau} O_p(n^{-\tau}) \right) ds.$$

In other words

$$\begin{aligned} \sqrt{k}\Omega_{n1}^* &= o_p(1) (n/k)^{1/2} \int_{1/k}^1 s^{\lambda-2} |\log s| |B_n(1 - ks/n)| ds \\ &\quad + o_p(k^{-\tau}) \int_{1/k}^1 s^{\lambda-3/2-\tau} |\log s| ds. \end{aligned}$$

The expectation of the first term of right-hand side of the previous equation is less than or equal to

$$o_p(1) (n/k)^{1/2} \int_0^1 s^{\lambda-2} |\log s| \mathbf{E}[|B_n(1 - ks/n)|] ds.$$

Using the fact that $E|B_n(1 - ks/n)| \leq (ks/n)^{1/2}$, we show that the previous quantity is less than or equal to $o_p(1) \int_0^1 s^{\lambda-3/2} |\log s| ds$. Since both integrals $\int_0^1 s^{\lambda-3/2-\tau} |\log s| ds$ and $\int_0^1 s^{\lambda-3/2-\tau} |\log s| ds$ are finite, then $\sqrt{k}\Omega_{n1}^* = o_p(1)$, as $n \rightarrow \infty$. $\square$